Global Environmental Change 69 (2021) 102228

Contents lists available at ScienceDirect

Global Environmental Change

journal homepage: www.elsevier.com/locate/gloenvcha

Trade-offs between physical risk and economic reward affect fishers' vulnerability to changing storminess

Nigel C. Sainsbury [a,*], Peter W. Schuhmann [b], Rachel A. Turner [a], Gaetano Grilli [c], John K. Pinnegar [d], Martin J. Genner [e], Stephen D. Simpson [f]

[a] Environment and Sustainability Institute, University of Exeter, Penryn, UK
[b] Economics and Finance, University of North Carolina Wilmington, Wilmington, USA
[c] CSERGE, University of East Anglia, Norwich, UK
[d] Centre for Environment, Fisheries and Aquaculture Science, Lowestoft, UK
[e] School of Biological Sciences, University of Bristol, Bristol, UK
[f] Biosciences, College of Life and Environmental Sciences, University of Exeter, Exeter, UK

ARTICLE INFO

Keywords:
Climate change
Changing storminess
Fisheries
Extreme weather
Vulnerability
Adaptation

ABSTRACT

Climate change-driven alterations in storm frequency and intensity threaten the wellbeing of billions of people who depend on fisheries for food security and livelihoods. Weather conditions shape vulnerability to both loss of life and reduced fishing opportunities through their influence on fishers' daily participation decisions. The trade-off between physical risk at sea and the economic rewards of continued fishing under adverse weather conditions is a critical component of fishers' trip decisions but is poorly understood. We employed a stated choice experiment with skippers from a temperate mixed-species fishery in southwest England to empirically assess how fishers trade off the risks from greater wind speed and wave height with the benefits of expected catch and prices. Technical fishing and socio-economic data were collected for individual fishers to identify the factors influencing trade-off decisions. Fishers preferred increased wind speed and wave height up to a threshold, after which they became increasingly averse to worsening conditions. Fishing gear, vessel length, presence of crew, vessel ownership, age, recent fishing success and reliance on fishing income all influenced the skippers' decisions to go to sea. This study provides a first insight into the socio-economic, environmental, and technical fishing factors that can influence the sensitivity of individual fishers to changing storminess. These insights can help to inform fisheries climate vulnerability assessments and the development of adaptation measures.

1. Introduction

Social-ecological systems, such as fisheries, involve complex connections between people, the natural resources they seek to exploit, and the governance institutions that shape the management of the system (Ostrom, 2009). Climate change is disrupting social-ecological systems at a global scale. Changes in the frequency and intensity of extreme weather events, such as storms, are some of the most conspicuous signs that our climate is changing (Hartmann et al., 2013; Feser et al., 2015; Murakami et al., 2017; Kossin et al., 2020). The potential impact of climate change on a social-ecological system can be explained by the system's climate vulnerability, which is defined as a function of its exposure and sensitivity to environmental change, and the adaptive capacity of the system (McCarthy et al., 2001; Adger, 2006). Assessment of climate vulnerability can enable policymakers to reduce climate change impacts by providing insights into adaptation actions (Marshall et al., 2013; Metcalf et al., 2015) and prioritising adaptation resources within and between systems (Monnereau et al., 2017).

Global fisheries are already experiencing the effects of climate change (Plagányi, 2019). Effects of climate stressors are expected to become more severe in future climate pathways (Adger et al., 2005), threatening the wellbeing of billions of people who rely on fisheries for livelihoods, food security and nutrition (Golden et al., 2016; FAO, 2016). There is a growing body of research suggesting that changes in future storminess will vary spatially, with increases in storm frequency and intensity in some regions, and reductions in storminess in others (Sainsbury et al., 2018). Already facing threats from ocean warming (Cheung et al., 2013), acidification (Ekstrom et al., 2015) and

* Corresponding author.
E-mail address: nigel_sainsbury@sfu.ca (N.C. Sainsbury).

https://doi.org/10.1016/j.gloenvcha.2021.102228
Received 29 June 2020; Received in revised form 14 December 2020; Accepted 19 January 2021
Available online 11 March 2021
0959-3780/

deoxygenation (Keeling et al., 2010), global fisheries must now also contend with changing storminess. Storms have the potential to disrupt fishing activities and cause extensive loss of assets, infrastructure and lives (Adger et al., 2005; Sainsbury et al., 2018). Attempts to assess the vulnerability of fisheries to climate stressors (for example, Allison et al., 2009; Monnereau et al., 2017) have only recently started to reflect the risk exposure of changing storminess (Pinnegar et al., 2019). The decisions that fishers make in different weather conditions are key social mediators of fisheries' vulnerability to changing storminess.

Studies that explore fishers' short-term decisions have thus far focused on biological and economic dimensions of fleet-level spatial behaviour (van Putten et al., 2012). Weather affects daily participation decisions (Huchim-Lara et al., 2016; Stobart et al., 2016), the fishing effort deployed at sea (Lopes and Begossi, 2011), how far fishers travel from shore (Macusi et al., 2015; Shepperson et al., 2016) and the depth of water fishers operate within (Naranjo-Madrigal et al., 2015). Fishers' expectations of trip catch, price and costs play a role in their individual short-term spatial effort decisions (Mistiaen and Strand, 2000). The unit price fishers expect to receive for their catch has a close connection to the weather. Adverse weather disrupts fishing effort. Such disruptions may reduce the supply of fish, driving up market prices, creating an economic incentive for fishers to go to sea in more extreme weather conditions (Abernethy et al., 2010). For example, decisions by skippers of large (20–24 m long) French trawlers in the face of worsening weather are predominantly price-driven (Morel et al., 2008). Despite the evidence of how fishers' decisions are affected by the weather, relatively little empirical evidence exists to explain fishers' daily participation decisions (whether or not to go to sea) in relation to weather and ocean conditions.

Fishing remains one of the most dangerous livelihoods on Earth (Roberts, 2010; Jensen et al., 2014; Fulmer et al., 2019). Given that fishers face great physical risks at sea yet must fish to meet their income requirements, their trip choices often involve trade-offs between physical risk and economic reward in conditions of great financial and environmental uncertainty (Smith and Wilen, 2005). Studies have explored fishers' financial risk appetite, with the majority finding fishers to be risk averse (Bockstael and Opaluch, 1983; Mistiaen and Strand, 2000; Smith and Wilen, 2005). Fishers' willingness to trade off financial returns for the risk of mortality has been calculated using fleet-level landings and fatality data for Alaskan crab fishers (Schnier et al., 2009). Yet few studies have sought to understand individual fishers' physical risk preferences, how they are traded off with economic reward, or the factors that affect these trade-offs (exceptions being Smith and Wilen, 2005; Emery et al., 2014).

Stated choice experiments are a particularly useful empirical economic methodology to understand individual preferences when observational data are not available, as is commonly the case in fisheries (van Putten et al., 2012). In the context of this study, preferences mirror the utility (satisfaction) derived from a feature of a fishing trip. Stated choice experiments require respondents to make choices between hypothetical alternatives defined by a set of attributes that take a range of discrete values (Johnston et al., 2017), and in doing so reveal individuals' relative preference for attributes and the trade-offs that they are willing to make between those attributes (Louviere, 2000). Stated choice experiments have been used extensively in health economics (de Bekker-Grob et al., 2012; Clark et al., 2014), environmental economics (Hoyos, 2010) and transport economics (Greene and Hensher, 2003; Hensher and Greene, 2003). For example, stated choice experiments are commonly used to explore how individuals trade off the health benefits and side effect risks of treatment options (Brett Hauber et al., 2013; Husni et al., 2017; Mühlbacher and Reed Johnson, 2016; Van Houtven et al., 2011) and have also been used to identify how tourists trade off hurricane risks with holiday rewards (Forster et al., 2012). Studies to understand fishers' trip preferences have most commonly employed revealed choice methods (for example, Smith and Wilen, 2005), which use observations of real choices to elicit preferences. Choice experiments have been used to assess risk preferences, but to our knowledge not in trade-offs between environmental risk and economic reward. We are only aware of one stated choice experiment that has been used to study commercial fishers' choice preferences (Eggert and Lokina, 2007) and it did not feature weather-related risks.

Previous studies of how fishers trade off physical risk and economic reward have analysed a narrow range of species, gear types, and vessel characteristics with very little comparison across these technical fishing dimensions or individual socio-economic factors. We address these research gaps, with the aim of informing a more thorough assessment of the vulnerability of fisheries to changing storminess, using a stated choice experiment to reveal fishers' willingness to trade-off weather-related risk and rewards. Further, we identify the role that vessel characteristics, gear type, and socio-economic factors play in shaping differences in individual preferences for catch, fish prices, wind speed and wave height in daily participation decisions. This study employed a stated choice experiment with skippers fishing from the temperate mixed fisheries in Cornwall, United Kingdom. The specific aims of the study were to: (1) empirically estimate preferences for wind speed, wave height, expected fish catch and expected fish price; (2) identify how preferences for weather conditions and economic reward differed relative to a number of individual-level technical fishing factors (e.g. vessel length and gear type); and (3) estimate how social and economic factors influence weather risk and economic reward trade-offs. The effect of higher wind speed and wave height on the likelihood of a fisher taking a trip was hypothesised to be negative, whilst higher fish catch levels and price were expected to increase the likelihood of a trip (Table 1). Based on key informant interviews and the literature, it was also expected that technical fishing and individual fisher factors would influence the role of weather variables in trip likelihood (Table 2). For instance, increasing age was predicted to increase aversion to wind speed and wave height, whereas increasing vessel length was expected to have the opposite effect.

2. Methods

2.1. Study area

The county of Cornwall forms the tip of the England's south-west peninsula. It has a centuries-old fishing industry, and its coast is dotted with small fishing villages and larger, more modern harbours, including Newlyn, which is England's second largest fishing port (McWilliams, 2014). A total catch of 18,790 tonnes with a value of £48,148,000 was landed in Cornwall in 2018 (MMO, 2019a). As of 1 September 2019, 526 fishing vessels were registered to a home port in Cornwall and the Isles of Scilly, of which 446 were under 10 m in length and 80 were 10 m or more, with a range of 3.9 m–34.8 m (MMO, 2019b). There are several vessel types in the Cornwall and Isles of Scilly fleet, ranging from small wooden punts using mixed gears through to large steel hull netters and trawlers. As of 2011 there were 1,300 people working in fishing and aquaculture in Cornwall and the Isles of Scilly (ONS, 2017), the majority of whom work in the fishing supply chain as Cornwall has a limited aquaculture industry. Cornwall has a mixed-species fishery with 36 species landed into Cornish ports in 2018, of which 22 were demersal, 10 were shellfish, and four were pelagic (MMO, 2019a). Fishing gear types used in Cornwall include crab and lobster pots, otter board trawls, beam trawls, ring nets (purse seines), gill nets, tangle nets and trammel nets, hand lines and dredges (McWilliams, 2014). Ring nets are classed as European Purse Seines (FAO, 2019) and target species that aggregate near the surface, most commonly European sardine *Sardina pilchardus*. Cornwall's harbours are exposed to prevailing south west winds and powerful swell waves from the North Atlantic, particularly to the west of Lizard Point, which provides protection to fleets operating further east in the English Channel (Fig. 1; van Nieuwkoop et al., 2013). Future storminess is projected to increase in Western Europe over the remainder of this century (Feser et al., 2015; Mölter

Table 1
Choice attribute details. Description of choice attributes varying across alternatives within choice sets including attribute levels with hypothesised effects shown for all variables.

Attribute	Description	Hypothesised direction of effect on trip likelihood	Hypothesis rationale	Attribute levels	Justification for inclusion
Wind speed	Wind speed in a favourable direction (mph)	Negative	Stronger winds and larger waves increase discomfort, create operating challenges and reduce safety.	10, 20, 30, 40, 50 mph	Christensen and Raakjær (2006) Gianelli et al. (2019) Interviews
Wave height	Wave height (metres)	Negative	Bigger waves increase discomfort, reduce the efficacy of some gear and reduce safety. Larger waves, particularly swells, may increase fishing success.	1, 2, 3, 4, 5 m	Emery et al. (2014) Interviews
Expected catch weight	Weight of landings a skipper expects to catch.	Positive	Trip decisions are influenced by the previous days' fishing. In adverse weather conditions, low catch expectations may reduce the likelihood of a skipper taking a trip.	Average – 50% Average Average + 50%	Lopes and Begossi (2011) McDonald and Kucera (2007) Interviews
Expected unit price	Market price the skipper expects to receive for their catch	Positive	Generally, as weather conditions deteriorate, supply of fish reduces driving up prices. Higher prices incentivise skippers to take greater weather risks.	Average – 50% Average Average + 50%	Morel et al. (2008) Abernethy et al. (2010) Interviews

et al., 2016).

2.2. Sampling and data collection

Stated choice surveys were administered face-to-face with commercial fishing skippers at seven harbours in Cornwall (Fig. 1) between May and July 2019. The sample was restricted to skippers, because even if a boat has crew and the skipper listens to their views, the skipper will make the final decision (Acheson, 1981). Locations were selected based on known size of the registered fleet so as to maximise the sample frame and to achieve a balance between gear types, vessel lengths and port locations on the north and south coasts of Cornwall. Fishers are a difficult group to access due to their time at sea and small population distributed among harbours separated by large geographic distances. As a result, a combination of convenience, stratified and snowball sampling was used (Faugier and Sargeant, 1997; Bryman, 2012). Skippers using otter board trawl, purse seines, passive nets (gill, tangle and trammel), hand lines and pots were included within the sample. Beam trawls and dredges were excluded because the population of skippers using these gears was insufficient to provide a large enough sample for these gear types. Harbours were visited at different times of day and fishers who were present on the quayside were approached opportunistically. Through snowball sampling, skippers who completed the survey were asked to provide contacts with other skippers. Although the snowball approach can be effective for sampling difficult-to-reach populations, including some fishers, the method does bring the risk of introducing bias towards people with greater social networks (Griffiths et al., 1993). A cumulative record was kept of respondents' technical fishing and socio-economic characteristics. As data collection progressed, characteristics with lower counts or limited ranges were increasingly targeted to maximise the statistical power of each variable.

2.3. Survey structure and facilitation

Data were collected through a survey comprising five sections: (1) questions about fishing practices including home port, the gear in use at the time of the survey, prior experience with impacts of extreme weather; (2) average landed catch weight and unit price by species; (3) trip choice questions to elicit preferences for wind speed, wave height, expected catch, expected price, and stated attribute non-attendance (Table 1); (4) reflections on the realism of the choice questions; and (5) technical fishing elements such as vessel length and power, socio-economic questions such as debt and household reliance on fishing income and age (Table 2).

To increase choice realism and reduce hypothetical bias, average trip catch and price data collected in survey section (2) were used to provide real respondent-specific values in the choice set in survey section (3) (Rose et al., 2008). Hypothetical bias exists when choices made by respondents differ between real and hypothetical decisions. Choice attributes and the first choice were explained to respondents to ensure their understanding of the structure of the choice sets. Skippers were asked to explain each of their choices to reduce the risk of respondents using non-compensatory decision processes, in which individuals do not consider the relative utility of all choice attributes across alternatives (Hensher et al., 2005; Hensher, 2006). Skippers were asked to make their choices based on the gear they were using, the species they were targeting, and the harbour they were fishing from at the time the survey was completed. Data collected in survey section (4) were sought to provide validity to the experiment by testing for hypothetical bias (Hensher, 2010). Show cards were given to respondents for questions relating to finances (Flizik, 2011) in survey section (5). The cards allocated a series of unique letters to monetary ranges for income and debt questions and were used to encourage responses to sensitive questions. Data from Section 5 were collected to test potential sources of preference heterogeneity.

Stated choice experiments typically assume that respondents have perfect cognition and use all the information available when making decisions (Puckett and Hensher, 2008). However, according to cumulative prospect theory (Kahneman and Tversky, 1992), humans have bounded rationality. When making decisions, individuals may use non-compensatory decision processes or heuristic coping strategies (Hensher et al., 2005; Hensher, 2006), such as attribute non-attendance, where only a subset of attributes are considered (Hensher, 2006). To mitigate the risk of attribute non-attendance introducing bias to coefficient estimates, respondents were asked after every choice which of the attributes they used in their decisions so this could be accounted for *ex-post* in the modelling process (Scarpa et al., 2013).

2.4. Choice experiment design

2.4.1. Choices, attributes and alternatives

The number of choices, alternatives and attributes were selected to reflect the expected sample size of 70–90 respondents (Orme, 2010) and to mitigate the risks of respondent fatigue, cognitive burden and non-compensatory decision processes (DeShazo and Fermo, 2002; Hensher, 2006; Hoyos, 2010). A blocked design (Hoyos, 2010) was adopted consisting of 20 choices in two blocks of ten. The two blocks of choices were presented to respondents alternately. Face-to-face administration

Table 2
Socio-economic and technical fishing factors to explain choice preference heterogeneity. Description of socio-economic and technical fishing variables fixed across choices but varying across individuals with hypothesised effects shown for all variables.

Attribute	Description	Hypothesised direction of effect on trip likelihood	Hypothesis rationale	Data type	Justification for inclusion
Vessel length *(effect on wind/wave)*	Registered length of vessel (m)	Positive for wind and wave	The longer the vessel, the greater its capacity to retain stability in adverse weather conditions.	Continuous	Christensen and Raakjær (2006) Interviews
Gear type *(effect on wind/wave)*	Fishing gear used at time of survey	Mix of positive and negative, and differing by wind and wave	Different gears are affected positively and negatively by weather conditions in different ways.	Categorical	Christensen and Raakjær (2006) Rezaee et al. (2016) Binkley (1991) Interviews
Power *(effect on wind/wave)*	Power of vessel engine in bhp	Positive for wind and wave	Increased power provides greater vessel control and capability to move in extreme sea states.	Continuous	Interviews
Port location	Location of port on north or south coast of Cornwall	Positive (for north relative to south) for wind and wave	The north coast (defined as being the west of Lizard Point) is more exposed to swell waves from the Atlantic Ocean. It is hypothesised that fishers will be more accustomed to, and therefore be less averse to, higher waves.	Binary categorical	Poggie et al. (1996) Interviews
Crew *(effect on wind/wave/ catch/price)*	Whether respondent regularly has one more crew onboard (yes/no)	Positive for price and catch, negative for wind and wave (for crew relative to no crew)	With crew there is a greater need to achieve higher income levels to ensure there is enough for all vessel employees.	Binary categorical	Eggert and Lokina (2007) Interviews
Age (*effect on wind/wave*)	Age of respondent	Negative for wind and wave	In general risk theory are people become older they become more risk averse.	Continuous (years)	Roalf et al. (2012) Interviews
Children under 18 (*effect on wind/wave*)	Whether respondent has children under the age of 18	Positive for wind and wave (for having children)	Having children creates greater financial need.	Binary categorical	Interviews
Boat owner or employee skipper *(effect on wind/wave/ catch/price)*	Whether the respondent owns the boat or not	Positive for wind, wave, catch and price (for owners relative to employee skippers)	Whilst the catch share is the same for a skipper whether they own the boat or not, an owner skipper is hypothesised to have a greater motivation because of the need to cover the vessel's fixed costs, which it is standard to take from vessel revenue before catch shares are calculated.	Binary categorica	Poggie et al. (1996) Binkley (1995) Interviews
Reliance on fishing income *(effect on wind/wave/ catch/price)*	Whether fishing is main source of household income	Positive for wind, wave, catch and price (for fishing being main household income source)	Greater reliance on fishing income creates greater financial need.	Binary categorical	Eggert and Lokina (2007) McDonald and Kucera (2007) Interviews
Debt *(effect on wind/wave)*	Total household and business debt liabilities relative to annual gross income	Positive for wind and wave	Greater debt relative to income creates greater financial need.	Continuous (ratio)	Interviews
Fishing success in preceding month *(effect on wind/wave/ catch/price)*	Rating of 1–5 based on combination of catch and price (1 = very poor, 5 = very good)	Increasingly positive as success decreases for wind, wave, catch and price	The level of fishing success (catch and price) in the previous month affects the financial need of the skipper.	Continuous (interval scale assumed to map to linear continuous variable)	Interviews

of the survey provided the opportunity to retain respondents' engagement in the choice-making process. To reduce hypothetical bias (Johnson et al., 2013), a literature review and qualitative interviews (N. Sainsbury, unpublished data) were used to identify realistic attributes and levels (Kløjgaard et al., 2012). Four attributes were selected for inclusion in the design (Table 1). Wind speed and wave height were chosen to reflect weather-related physical risk and given units most commonly used by local fishers (mph and m respectively). Expected fish catch weight (kg) and price (£/kg) were selected as measures of fishing reward. Respondents were instructed to assume that other attributes that might affect trip decisions were constant across all the choices: favourable wind direction and stage of lunar tidal cycle; forecasted continuation of wind speed and wave height attribute levels for the week ahead; passive gear is at sea and needs to be hauled; and quota is available to land whatever target species are caught.

Five discrete levels were chosen for wind speed and wave height and three levels for expected catch weight and expected price. Attribute values were selected based on interviews and chosen to reflect all but the most extreme conditions for the vessel sizes and gear types within the sample frame (Table 1). To ensure relevance to every respondent, expected catch and price attribute levels pivoted around each respondent's average value (pivoted values: average, average minus 50%, average plus 50%). The display of expected fish price and catch weight attributes within choice sets included both the pivoted value and the real respondent-specific values based on their declaration of average daily catch and price by species (Fig. 2). Given the known sample size limitations, and following Eggert and Lokina (2007), the design included three unlabeled alternatives (trip 1, trip 2, no trip) to maximise the statistical power of each choice decision (Fig. 2). The 'no trip' alternative was included to avoid the bias associated with forcing respondents to choose between alternatives when they would prefer neither (Hanley et al., 2002). This was particularly important for making the choice sets realistic given the nature of fishing trip decisions.

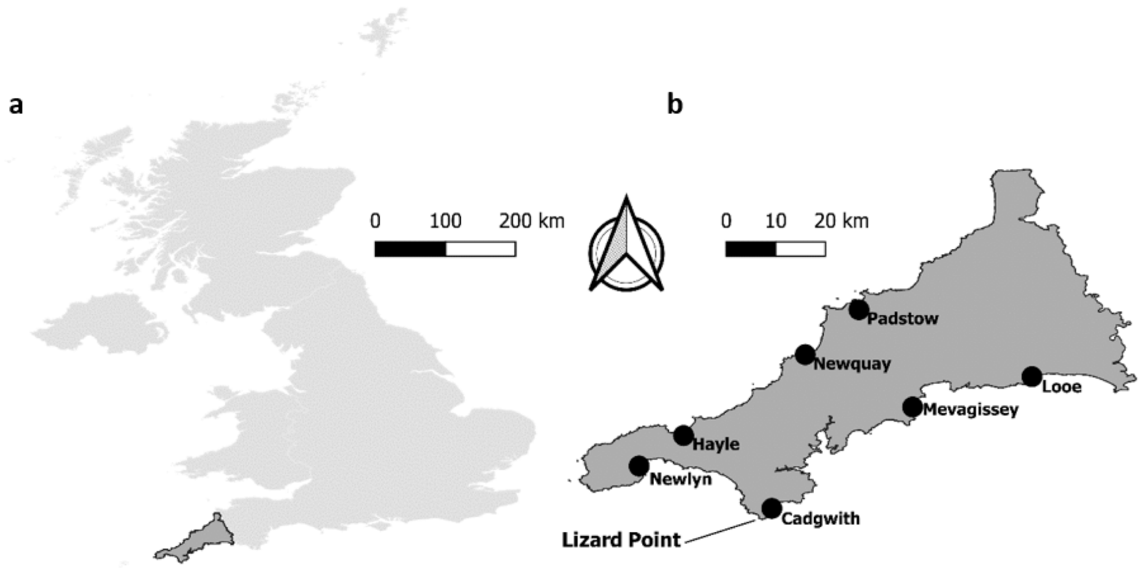

Fig. 1. The study area. (A) United Kingdom highlighting location of Cornwall. (B) Cornwall showing the locations of the seven ports used for data collection. Lizard Point, used to categorise ports as north or south coast, is also shown.

CHOICE 1 PLEASE CHOOSE ONE OF THE THREE OPTIONS: TRIP 1, TRIP 2, OR NEITHER

		TRIP 1	TRIP 2	
Wind speed		20 Mph equivalent to 17 knots	40 Mph equivalent to 35 knots	
Wave height		3 Metres equivalent to 10 foot	3 Metres equivalent to 10 foot	
Expected fishing success (weight)		Average - 50% Based on the average catch you supplied, this would be: 75 Kg	Average + 50% Based on the average market price you supplied, this would be: 225 Kg	
Fish price (£/kg)	£/Kg	Average - 50% Based on the average market price you supplied, this would be: Monk £5.00 Ray £1.75 Turbot £6.50 Brill £5.00 Spider crab £0.75	Average Based on the average market price you supplied, this would be: Monk £10.00 Ray £3.50 Turbot £13.00 Brill £10.00 Spider crab £1.50	
1. Which trip would you choose?		TRIP 1 1	TRIP 2	I WOULD CHOOSE NEITHER TRIP

Fig. 2. Choice experiment presentation. An example choice set with pivoted expected catch and expected fish price values shown for an example individual respondent.

2.5. Pilot and Bayesian d-efficient design

A pilot was carried out with three fishers, who each employed different gear types and were based at different harbours. This pilot helped to refine the framing of the experiment and the choice attributes and levels. Limitations of cognitive burden and respondent fatigue prevent the use of fully orthogonal choice experimental designs, necessitating efficient designs that maximize statistical power within acceptable levels of experiment complexity (Scarpa and Rose, 2008; Bliemer and Rose, 2011). The experimental design was carried out using a Bayesian d-efficient approach (Bliemer and Rose, 2011) in Ngene software (Choicemetrics, 2018). In the d-efficient approach, the determinant of the variance–covariance matrix is calculated based on different combinations of choice attribute values and the design with the lowest determinant is selected. Design rules were used to prevent dominant choice alternatives and unrealistic choice scenarios (Crabbe and Vandebroek, 2012). The Bayesian d-error of the final design was 0.0194.

2.6. Data preparation

Discrete and continuous versions of wind speed and wave height variables were created so that models could be estimated with discrete variables first to check for non-linear relationships. The expected price attribute levels presented to respondents (average, average plus 50%, and average minus 50%) were converted to mean fish prices (in £/kg) for each individual using a weighted-mean calculation based on their real species catch composition values. Individual harbours were coded into a new binary north or south coast categorical variable based on their position relative to Lizard Point (Fig. 1). To preserve the ordinal information provided by fishing success in the preceding month, this independent variable was treated as a continuous linear variable. Categorical covariates were effects coded (Hensher et al., 2015a) to avoid confounding with the null-coded opt-out “no trip” choice alternative (Daly et al., 2016). Attribute levels in choice tasks where the respondent stated they did not use the attribute in their decision-making process were coded using NLOGIT 6 (Econometrics Software Inc., 2019) in order to prevent the associated attribute(s) from influencing the model estimation, thereby removing bias caused by attribute non-attendance. Checks for multi-collinearity between covariates were carried out through mixed factor analysis in R (R CoreTeam, 2019) using the *FactoMineR* package (Lê et al., 2008) and by checking the stability of model coefficient estimates after removal of potentially multi-collinear variables. Vessel power and length were found to be collinear. As a result, vessel power was removed from the analysis. Some respondents did not respond to the income and debt questions, and so these variables were removed from the analysis due to missing values.

2.6.1. Analytical approach

Each of the 30 observations generated by each respondent (ten choices, three alternatives) contained data describing the levels of the four attributes for each alternative within a choice (or zeros in the case of the third, 'no trip' option within each choice set), individual-specific socio-demographic and technical fishing covariates, and a binary response variable indicating the chosen alternative. Respondents inferred the negative risks (e.g. physical danger, personal discomfort and threat to fishing assets) from the wind and wave levels of the choice attributes but were given specific trip rewards (fish catch and price) resulting from each trip alternative. Conditional logit (CL) and random parameter logit (RPL) models were estimated in NLOGIT 6 (Econometrics Software Inc., 2019). The models are specified in the Appendix. Quadratic terms were included for wind speed and wave height based on evidence from a conditional logit model with discrete versions of these variables. The inclusion of quadratic terms in the specification of the utility function for choice experiments allows the estimation of the diminishing marginal utility of an attribute (van der Pol et al., 2010). CL and RPL models were selected using stepwise deletion on models containing all choice attribute variables and interactions between choice attribute variables and technical fishing or socio-demographic variables with the objective of parsimony. The procedure involved the iterative removal of the least statistically significant continuous predictor variable or level of a categorical variable with a p-value over 0.05, until the models contained only variables statistically significant at the 95% level. Minimum adequate models were compared to null models using likelihood ratio tests. The magnitude and sign of coefficients on omitted (reference) levels of effects-coded covariate interactions were derived by taking the negative sum of the coefficients on the remaining attribute levels from the minimum adequate CL model (except gear type, for which the full CL model before stepwise deletion was used) (Bech and Gyrd-Hansen, 2005).

3. Results

3.1. Respondent characteristics

In total, 80 skippers fishing in Cornwall responded to the survey, of which 78 had their registered home port in Cornwall and the remaining two fished seasonally from Newlyn but were registered elsewhere. Newlyn and Mevagissey contributed 32 and 27 responses respectively, with the remainder obtained from smaller ports. Of the total sample, 47 (59%) of respondents fished from the north coast of Cornwall and 34 (41%) fished from the south coast. Vessel lengths ranged from 4.8 m to 22 m, with a mean length of 10.7 m (±0.46 SE). The most frequently sampled gear type was passive nets (n = 29), followed by pots (n = 21), otter board trawl (n = 17), hand lines (n = 9) and purse seine (n = 4).

The 78 respondents registered in Cornwall represented 15% of all vessels with registered home ports in Cornwall, and by vessel length category represented 9% of the under 10 m vessels and 52% of the 10 m and over vessels. The mean age of respondents was 49 years (±1.4 SE) and ranged from 22 to 77 years. The mean fishing success rating over the month preceding survey completion was 2.85 (±0.15 SE) with a minimum of 1 and maximum of 5 (on a scale from one to five, where 1 was very poor and 5 was very good). Fishing was the main household income for 76% of respondents, 45% of respondents had children under 18 years of age, 84% of respondents owned their vessel, 64% fished with one or more crew members regularly, and all respondents were male. All respondents completed all choice sets. The sampling strategy was not random and therefore precluded generalisation of the Cornish fleet. However, the sample size and resultant number of choices made was sufficiently large to provide the statistical power required to analyse how weather risk and fishing rewards affect fisher trip decisions across individual-level covariate factors.

3.2. Modelling results

The CL and RPL models contained statistically significant parameter mean estimates for all main choice attribute variables (Table 3). Linear and quadratic terms for wind speed and wave height were found to be statistically significant in both models (Table 3). The negative quadratic coefficients for wind speed and wave height showed that the utility skippers derive from wind speed increases, peaks, and then decreases as wind speed and wave height increase (Figs. 3 and 4). The magnitude of the quadratic coefficients determine the shape of the curve and the linear coefficient determines the position of the curve. The greater the negative quadrative coefficient of a variable, the faster aversion to that variable falls after the peak. An increase in the positive linear coefficient shifts the curve up and to the right, decreasing aversion at any given wave height or wind speed. Both models had several statistically significant interaction terms between covariates and main attributes, providing strong evidence of heterogeneity in attribute preferences across individuals (Table 3).

Aversion to weather attributes varied across all gear types (Table 3; Figs. 3 and 4). Skippers using purse seines were less averse to wind speed (linear term in CL model) and more averse to wave height (quadratic term in both models) than the mean aversion to wind speed. Skippers using passive nets were less averse to wave height (quadratic term in both models) than the mean aversion to wave height. In both models those using hand lines were less averse to wind speed (quadratic term in both models) and wave height (quadratic term CL model), whilst skippers using pots were more averse to wind speed (linear term in CL model) than the mean of all fishing methods. Using the negative sum of the coefficients on the other gear types in the full CL model, skippers using otter board trawls were found to be more averse to wave height (linear and quadratic terms), less averse to wind speed (linear term) and more averse to wind speed (quadratic term). Respondents with longer vessels were less averse to wave height (quadratic term in CL model) and wind speed (quadratic terms in both models).

Social and economic factors interacted with the main choice attributes in both final models (Table 3; Figs. 3 and 4). Respondents who worked single-handed were less averse to wind speed (quadratic term in CL model) and placed less value on expected catch in their trip decisions than those working with crew. Use of crew did not feature in the final RPL model. Skippers who were not the main income provider in their household were more averse to wind speed (quadratic term in both models) and placed a higher value on catch (linear term in both models) in their decisions. Respondents who did not own their boat placed lower value on expected catch than those who did own their boat in both models. Similarly, respondents with better fishing success over the month preceding the survey were found to place less value on expected catch in their trip decisions in both models. Older respondents were more averse to larger waves (quadratic term in CL model) but less averse to increasing wind speed than younger skippers (quadratic term in both models).

Respondents who were not the main household income provider were more averse to wind speed (quadratic term in both models) and placed a higher value on expected catch than those who were the main income provider (both models). Having children under the age of 18 and port location on the north or south coast were not found to statistically significantly affect preferences for any of the main attributes in the CL model and therefore did not feature in the RPL modelling process.

Table 3
Choice experiment modelling results. Model coefficient estimates for models explaining the effect of choice attributes and their covariate interactions on trip decisions. Statistical significance at the 99% level is denoted by *** and at the 95% level by **. In the random parameter logit model, all attributes are random effects except wave height, which was treated as a fixed parameter. Coefficient estimates and confidence intervals are in logits. Reference levels for categorical covariates are otter board trawl gear, skipper works with crew, skipper is main household income provider, and skipper owns vessel. Full model results can be found in the Supplementary materials.

Variable	Conditional Logit				Random Parameter Logit			
	Coefficient estimate		2.5% CI	97.5% CI	Coefficient estimate		2.5% CI	97.5% CI
Choice Attributes								
Wind speed	0.09344	***	0.04401	0.14286	0.12772	***	0.06448	0.19096
Wave height	1.16763	***	0.72327	1.61198	1.31883	***	0.73907	1.89859
Expected catch weight	0.00306	***	0.00203	0.00408	0.00329	***	0.00192	0.00465
Expected price	0.18274	***	0.13789	0.22759	0.57539	***	0.38247	0.76831
Wave height^2	−0.25956	***	−0.37097	−0.14816	−0.32861	***	−0.4377	−0.21951
Wind speed^2	−0.00674	***	−0.00848	−0.00500	−0.01129	***	−0.01474	−0.00784
Technical fishing interactions								
Gear type								
Wave height^2 * purse seine	−0.18776	***	−0.25183	−0.12369	−0.19321	***	−0.28333	−0.1031
Wind speed *purse seine	0.06417	***	0.02807	0.10028	–		–	–
Wave height^2 *passive nets	0.08239	***	0.05347	0.11131	0.1475	***	0.09019	0.20481
Wave height^2* hand line	0.08048	***	0.03441	0.12655	–		–	–
Wind speed^2 * hand line	0.00074	**	0.00010	0.00137	0.0021	***	0.00119	0.00301
Wind speed * pots	−0.03121	**	−0.05040	−0.01203	–		–	–
Vessel length								
Wave height^2 * vessel length	0.01060	***	0.00575	0.01545	–		–	–
Wind speed^2 * vessel length	0.00010	***	0.00004	0.00016	0.00017	**	0.00006	0.00027
Social and economic interactions								
Regular presence of crew								
Wind speed^2 * no crew	0.00050	***	0.00023	0.00077	–		–	–
Expected price * no crew	−0.06142	***	−0.10351	−0.01934	–		–	–
Reliance on fishing income								
Wind speed^2 * skipper not main household income provider	−0.00108	***	−0.00144	−0.00072	−0.00129	***	−0.00195	−0.00063
Expected catch weight * skipper not main household income provider	0.00195	***	0.00097	0.00292	0.00163	**	0.00034	0.00292
Vessel ownership								
Expected catch * vessel not owned by skipper	−0.0007	***	−0.00098	−0.00041	−0.00101	***	−0.00142	−0.0006
Fishing success								
Expected catch * fishing success in preceding month	−0.00011	***	−0.00017	−0.00004	−0.00015	***	−0.00024	−0.00006
Age								
Wave height^2 * age	−0.00235	***	−0.00370	−0.00101	–		–	–
Wind speed^2 * age	0.00003	***	0.00001	0.00005	0.00004	**	0.00001	0.00008
Alternative specific constants								
ASC: Trip 1	−0.06850		−0.81120	0.67420	−0.19624		−1.10694	0.71446
ASC: Trip 2	0.18626		−0.54742	0.91994	0.06111		−0.83538	0.95759
Distribution of random parameter (standard deviations)								
Wind speed	–		–	–	0.04690	***	0.01966	0.07415
Wind speed^2	–		–	–	0.00092	**	0.00020	0.00164
Wave height^2	–		–	–	0.08787	***	0.05156	0.12418
Expected catch	–		–	–	0.00000		−0.00009	0.00009
Expected price	–		–	–	0.36954	***	0.22011	0.51897
Key model metrics								
AIC	961.8				927.9			
Pseudo R^2	0.4525				0.4971			
Log-likelihood	−456.89				−441.96			

4. Discussion

By taking a human behavioural perspective, this study provides a unique contribution to understanding how changing storminess can impact fisheries. We employed a stated choice experiment, a robust experimental methodology, in a novel context to identify for the first time how fishers value and trade off weather-related physical risk and fishing rewards in their daily participation decisions. We have shown that fishers' trade-offs of physical risk and fishing rewards are influenced by technical fishing, social and economic factors. This study can help inform how fisheries vulnerability to changing storminess is considered and assessed, and provides insights for policymakers regarding potential adaptation actions.

4.1. The role of weather, expected catch and expected price in fishers' trip decisions

Fishers are more likely to take a fishing trip when they expect to catch more fish and achieve a higher price for the fish, but this preference can be overridden when weather-related risks become too great. Skippers' showed a preference for increasing wind speed and wave height up to a threshold, above which they became increasingly averse to them. Previous findings have shown that fishers have a simple aversion to higher wind speeds and larger waves (Smith and Wilen, 2005; Christensen and Raakjær, 2006; Emery et al., 2014; Gianelli et al., 2019). The initial increase in preference for wave height was stronger than for wind speed, suggesting that there are benefits of fishing in perturbed sea states. Previous work has shown that catches change during and after perturbed sea states (Ehrich and Stransky, 1999). The underlying reasons are not clear, but may relate to changes in turbidity promoting active feeding by target fish, reducing target fish visual

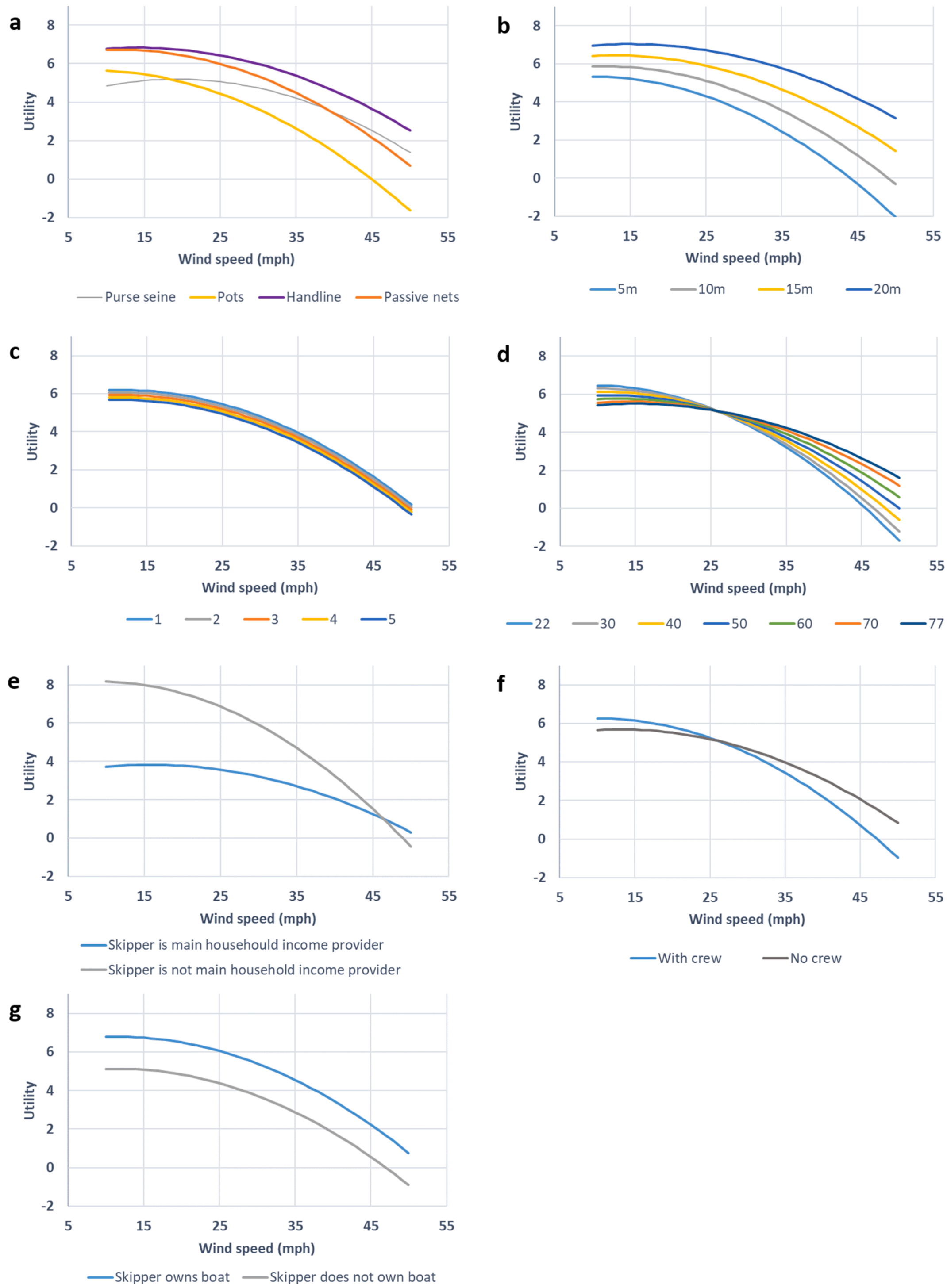

Fig. 3. Utility curves for wind speed (utility can be considered akin to satisfaction). Utility is in logits. Plots showing conditional logit model predictions of how the aversion to wind speed varies with (a) gear type, (b) vessel length, (c) fishing success in preceding month, (d) age, (e) reliance on fishing income, (f) use of crew, (g) vessel ownership. Except for the variable highlighted in each graph and wind speed, other variables are held constant at their mean.

acuity, and causing temporary evacuation from the area.

Fishers' aversion to higher wind speed may result from the role it plays in elevating the risk of at-sea vessel accidents (Jin and Thunberg, 2005; Lincoln and Lucas, 2010; Rezaee et al., 2016), escalating physical risks (Smith and Wilen, 2005), and increasing fuel costs (Abernethy et al., 2010; Bastardie et al., 2013). The reduction in fisher utility after preferences for wave height peak reflects existing evidence that fishers are averse to higher wave heights (Emery et al., 2014). Aversion to larger waves may be explained by higher wave heights predicting more severe (Wu et al., 2005) and more frequent (Wu et al., 2009) vessel accidents, increased the risk to boats and fishers (Niclasen et al., 2010), reduced gear efficacy and therefore catch (Stewart et al., 2010), and increased risk of gear damage (Holland, 2008).

4.2. Individual fisher preference heterogeneity

4.2.1. Technical fishing factors

Variations in fishers' preferences for wind speed, wave height,

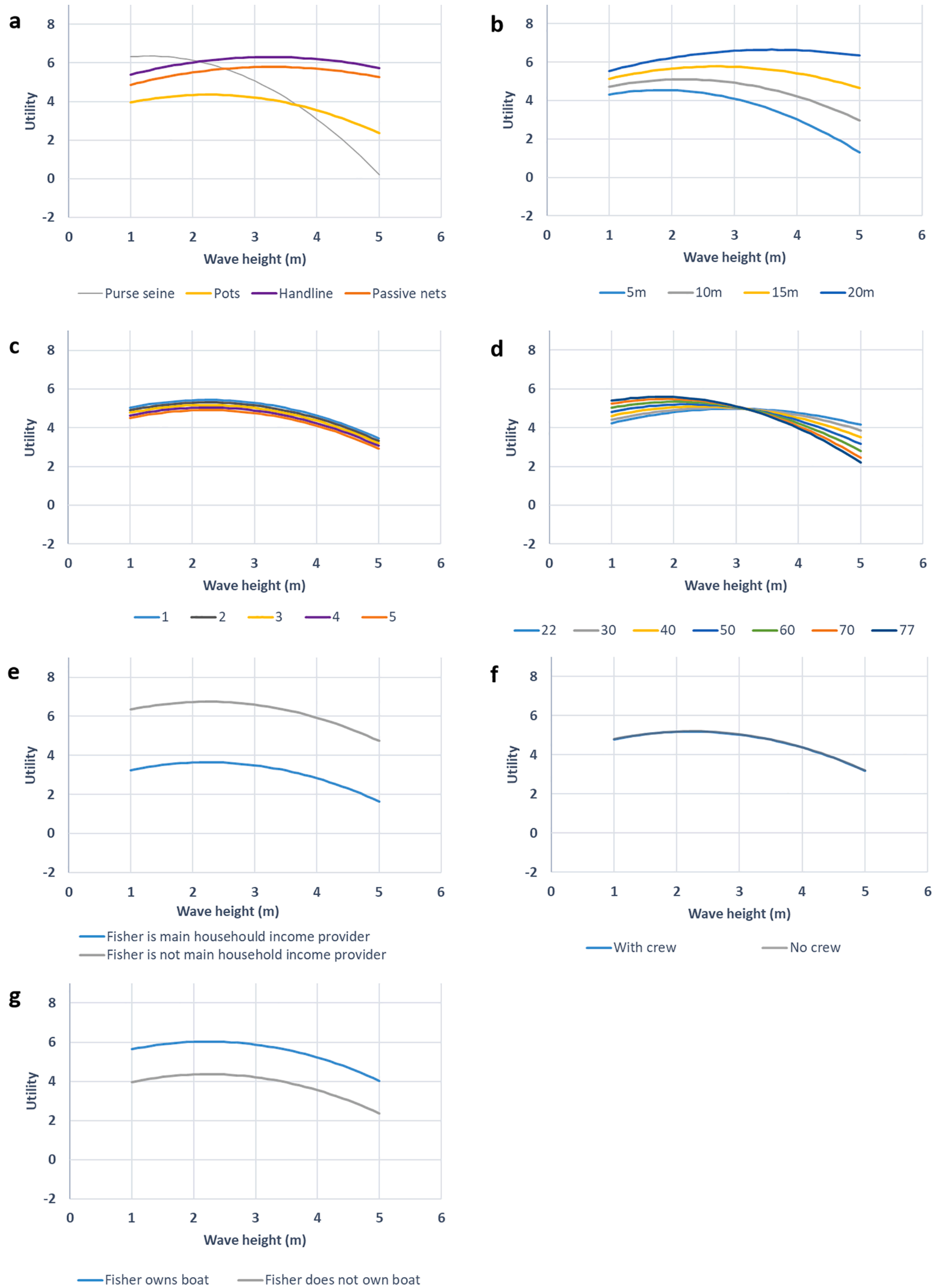

Fig. 4. Utility curves for wave height (utility can be considered akin to satisfaction). Utility is in logits. Plots showing conditional logit model predictions of how the aversion to wave height varies with (a) gear type, (b) vessel length, (c) fishing success in preceding month, (d) age, (e) reliance on fishing income, (f) use of crew, (g) vessel ownership. Except for the variable highlighted in each graph and wave height, other variables are held constant at their mean.

expected catch and expected price are linked to technical aspects of gear operation and the ecology of target species. Skippers using passive net gears had below average aversion to wave height. Although passive net fishing efficacy is only adversely affected by the most extreme weather, large waves increase the risk of gear loss. Passive net skippers' lower aversion to wave height may reflect an incentive to avoid losing valuable net assets damaged and relocated by large waves and to haul the fish aboard rather than allow them to spoil whilst they wait out the storm. Increased turbidity in shallower demersal zones caused by large swell waves may also play a role in making otter board trawl skippers more averse to wave height. The efficacy of otter board trawls for capture of round fish is diminished by turbidity as this reduces the ability of target fish to see the sand clouds stirred up by trawl doors and bridles, which herd fish into the net (Main and Sangster, 1981; Dickson, 1993). Conversely, turbidity can increase the catchability of gill nets (Murphy, 1959; Olin et al., 2004), as fish are less likely to see and avoid them.

Trawl efficacy for round fish relies on a consistent trawl towing speed, which is reduced by adverse weather (Weinberg and Kotwicki, 2015). Furthermore, the catchability of flat fish by otter board trawls in large waves may be reduced by inconsistent contact between trawl bridles and the sea bottom (Somerton, 2003) and decreased trawl net spread (Queirolo et al., 2015).

Strong winds make it difficult for a skipper to maintain a vessel's position to safely haul pots, which may explain the above average aversion to wind speed shown by skippers using pots. As with passive nets, the incentive for pot skippers to rescue their gear and its catch may reduce their aversion to wind speed, although shellfish tend to take longer to spoil than whitefish. However, if crabs and lobsters are left too long in pots there is the risk of escape (Muir et al., 1984; Zhou and Shirley, 1997), damage from fighting and, in the case of lobsters, cannibalism (Jacklin and Combes, 2007).

Users of purse seines were found to have above average aversion to wave height and below average aversion to wind speed. The greater aversion to wave height may be associated with the destabilising nature of the fishing method. Catching upwards of ten tonnes in one net, the catch is held on one side of the vessel whilst it is transferred onto the boat. This creates a stability risk to the vessel that is exacerbated by large waves (Ben-Yami, 1987). Purse seine skippers' greater preference for wind speed may reflect the inshore location of their fishing grounds, and echoes evidence that tuna purse seine fishers in the Seychelles avoid fishing locations with either very low or very high wind speed (Davies et al., 2014). Hand line skippers also tend to fish inshore, which may explain why they are less averse to high wind speed and wave height than the mean of other gears, as all choices were based on an assumption of a favourable wind direction, which would allow them to fish comfortably in lee of the land. Furthermore, the efficacy of hand lines is not known to be negatively affected by wind or waves in the same way as some other gears, such as trawls.

Vessel length is an important factor in the safety of vessels at sea because vessel stability is in part a function of the vessel length to wavelength ratio (Niclasen et al., 2010). Smaller vessels are more likely to be involved in accidents at sea caused by wind (Jin and Thunberg, 2005). Our findings of the influence of vessel length on wave height aversion do not support those of Emery et al. (2014), who found that vessel length did not interact with wave height in decisions to go to sea. The lack of evidence for port location affecting wind speed and wave height preferences suggests that the differences in swell conditions between the north and south coasts of Cornwall does not affect the role of wind speed or wave height in skippers' short-term decisions.

4.2.2. Social factors

The increased aversion to wind speed that skippers had when working with crew may result from the close relationship between crew and skipper (Urquhart et al., 2011). Skippers feel a sense of responsibility to ensure the safety of their crew and to avoid the discomfort of extreme weather, especially if expected trip revenue is low. The labour market for crew in Cornwall has a shortage of people with the requisite skills (Cornwall Rural Community Charity, 2016), which may create competition between skippers for the best crew and cause skippers to be more empathetic to crew's wind speed preferences. The greater preference for a trip with higher expected fish prices shown by skippers working with crew compared to those working single-handed may reflect social and economic aspects of the relationship between skipper and crew. Skippers need to earn a greater income when working with crew in order to provide them with sufficient catch share income, and are motivated by the responsibility they feel for the welfare of their crew when revenues are low (Holland, 2008). In addition, skippers may need to provide a stable income to their crew in order to retain their services (Marine Scotland Science, 2014).

The age of skippers also affected their trip preferences. The increased aversion to wave height with age reflects the effect of age on risk disposition generally, whereby people become more risk averse as they get older (Dohmen et al., 2011; Mata et al., 2016). The combination of increasing physical disability with age and the discomfort associated with fishing in large waves may explain the greater aversion to higher wave heights of older skippers. The effect of age reducing aversion to higher wind speeds may reflect downsizing to smaller boats as skippers wind down their fishing careers. Small boats fish close to shore, which would allow skippers to benefit from fishing in the lee of the land during the favourable (presumed to be offshore) wind direction assumed in this experiment.

4.2.3. Economic need

We have shown that greater economic need results in lower aversion to physical risk. Skippers for whom fishing provided the main source of income to their household showed less aversion to higher wind speed. Their willingness to take greater physical and economic risk from fishing in higher winds reflects their need to do so. This corresponds with risk sensitivity theory, which posits that individuals with greater need take greater risk when lower risk options will not meet their needs (Mishra and Lalumière, 2010).

Economic need also affected preferences for expected catch, but in multiple complex ways. Skippers showed a greater preference for catch in their trip decisions where they owned their vessel or had experienced worse fishing success in the previous month. In Cornwall, fishers are paid on a crew share system in which trip profits are split amongst the crew. The skipper's share of trip profits is the same whether they own the boat or not. However, owner skippers may have a greater motivation than employed skippers to maximise their revenues in order to contribute to the boat's fixed costs, such as debt repayments and maintenance. Fishers in households less reliant on fishing income are less likely to take trips when expected catch is low because they have less need to and can be more selective in the trips they take.

4.3. Implications

The negative quadratic shape of skippers' aversion to wind speed and wave height means that the likelihood of fishers choosing to go to sea reduces at an accelerating rate as wind speed and wave height increase. This suggests that the disruptive effect on fishing activity of any future increased storminess may be non-linear and potentially more severe than might be expected under a linear assumption. The fisheries literature has rightly identified that changing storminess will impact fisheries through an increase in frequency of the most extreme events (Allison et al., 2009; Badjeck et al., 2010; Cheung et al., 2012). However, our findings suggest that a shift in the distribution of storm frequency and intensity will impact fisheries at all levels of storminess, not only the extremes. Whilst such a shift in the distribution of storms may increase the frequency of extreme weather events, it will also increase the frequency of moderate severity storms. Most fishers will find their participation decisions routinely affected by this shift in moderate conditions leading to a gradual reduction in the days they choose to go to sea, or an increase in the physical risks to which they are exposed. The impact of changing storminess on fisheries is therefore more complex than the simple narrative focusing only on extreme events.

The role of technical fishing and socio-economic factors in how skippers trade off physical risk and economic reward confirms that individual skipper characteristics affect the sensitivity of fishers to changing storminess. In the same way that the ecological sensitivity of a fishery to ocean warming is determined by the biological and ecological characteristics of a target species, so conceptualisations of fisheries sensitivity must reflect the role of skippers' technical fishing and socio-economic characteristics in direct socio-economic impacts of changing storminess. As well as direct impacts on target species and their habitats with indirect socio-economic impacts, changing storminess is likely to have direct socio-economic impacts (Sainsbury et al., 2018). These direct socio-economic impacts will alter fishing activities, which may lead to indirect ecological impacts. The linkages between socio-economic and ecological impacts remain unclear. Our findings suggest that fisheries vulnerability assessments should reflect the multi-faceted socio-ecological impact of changing storminess.

Changing storminess poses two direct threats to fishers: disruption to their fishing activities (economic losses from choosing to stay in port); and the physical threat to the fisher themselves (injury and death) and to their assets (their boats and gear). How an individual fisher trades off physical risk and economic reward in daily participation decisions will determine how sensitive that fisher is to alterations in the physical and disruptive risks of changing storminess. If a skipper chooses to stay in port in the face of adverse weather, they eliminate the physical risk of being at sea but bear the full economic loss of a missed fishing day. Alternatively, by choosing to go to sea in adverse conditions, skippers accept a higher risk of injury, death or asset loss but reduce the risk of lost income. Changing storminess therefore impacts different people in different ways and begs the question, "who is sensitive to what?" By taking additional physical risks in adverse weather, fishers are personally sensitive to disability and loss of life, with emotional and socio-economic consequences for their families. Conversely, by staying ashore and avoiding physical risk, fishers protect themselves from the hazards of the sea but expose themselves, their family and potentially the broader local supply chain and community to negative socio-economic impacts.

When aggregated across a fleet, fishers' individual daily participation decisions amalgamate to form a community level sensitivity to changing storminess. The technical fishing and socio-economic factors we identified as influencing skippers' decision trade-offs can therefore affect how sensitive a fishery is to the direct socio-economic impacts of changing storminess. For instance, if a fishery has consistent technical or socio-economic characteristics, such as reliance on a single gear or high economic need, then this will strongly influence its sensitivity. Fisheries climate vulnerability assessments require aggregate measures of sensitivity in order to be practical. Our findings provide important insights to help guide the development of measures of fisheries sensitivity to changing storminess. National measures of mean and range of vessel lengths, proportion of gear types used, level of economic need, proportion of vessels using crew, and skipper age may help inform vulnerability assessments. Challenges may exist in developing these measures due to limited availability of detailed data, particularly in tropical and small-scale fisheries.

The technical fishing and individual fisher characteristics governing fishers' trade-off decisions can help inform adaptation to changing storminess as part of the transition to climate resilient fisheries. Protecting fishers from income and fishing asset losses due to storm events would reduce their motivation to take greater physical risk out of economic need. Supporting fishers to move to less sensitive gear types and vessel sizes will help reduce the physical and disruption risks, as fishers may not have the available assets to make this transition unaided. Fisheries management policies that either deliberately, or incidentally, lead to changes in target species, gear types, the vessel profile of a fleet, or the economic viability of skippers using crew should account for the possible effect on fishers' sensitivity to changing storminess. Changes in local storminess will alter the distribution of wind speeds and wave heights, but changes in storminess in distant areas of the same ocean basin may also increase the frequency of large swell waves reaching a fishery's waters. Understanding the exposure of a fishery separately to wind speed and wave height is important for making adaptation decisions.

5. Concluding remarks

Global capture fisheries and other food-producing systems face a number of climate stressors that threaten the coastal communities that depend upon them, and research is required to deepen our understanding of the vulnerability of fisheries to changing storminess. Building upon this study of a mixed temperate fishery, it would be valuable to identify differences in weather-related decisions across countries and cultures, marine and inland fisheries, fishery types, ecosystems, and regional and local geo-physical and spatial contexts. Exploring at-sea decisions and the role of meteorological and oceanographic factors not used in this study, such as wind direction and lunar tidal cycle, could be critical to developing a broader evidence base for fishers' weather-related decisions. Using stated choice experiments in fisheries can be improved by acknowledging the large degree of uncertainty in fishers' trip decisions. Whilst random utility theory is the most commonly adopted framework for choice experiments, and was employed for this study, expected utility theory (Fishburn, 1988) and cumulative prospect theory (Kahneman and Tversky, 1992; Li and Hensher, 2017) provide alternatives for reflecting choice under uncertainty and risk. As fishers do not know with certainty what weather they will actually encounter at sea, how much they will catch, or the price they will receive for it, there is also potential for future studies to represent this uncertainty in choice attributes levels, following examples in transport and health economics (Hensher et al., 2011; Harrison et al., 2014). The cumulative effect of successive storms on fisher decisions and adaptive capacity also requires further investigation.

Understanding the vulnerability of fisheries to climate change and identifying actions to support their adaptation is critical to reducing negative impacts on fishing communities. This study provides evidence that the decision-making of natural resource users affects the climate vulnerability of a social-ecological system, and that technical, social and economic factors are important in mediating this effect. These sources of heterogeneity indicate that adaptation to changing storminess should focus on protecting fishers' assets to reduce the economic need for fishers to take high levels of physical risk, for instance through climate risk insurance (Surminski et al., 2016; Sainsbury et al., 2019), and facilitating access to less sensitive gear types and vessels, for instance through improving access to microfinance (Cull and Morduch, 2018). However, fisheries managers should take care to manage any trade-offs between reduced vulnerability and fisheries management goals, and pursue policies that support the adaption and sustainability of fisheries. Whilst this study provides insight into one aspect of the sensitivity of fishers to changing storminess, further research is required to quantify the socio-economic vulnerability of, and economic impact on, fisheries and individual fishers. Projections of exposure of fisheries to changing storminess, and the consequential effect on the annual distribution of wind speeds and wave heights, are a necessary first step. In addition, the capacity of fishers to adapt to changing storminess (Cinner et al., 2018) requires attention, because it would affect the ability of fishers to mitigate the magnitude of socio-economic impacts. For instance, it will be important to understand the flexibility of fishers to switch fishing gears or fishing location, which may be determined by the prevailing management regime. It would also be valuable to understand the potential for any fisher assets to be used to make resilience-enhancing vessel alterations. Progress towards quantified vulnerability and impact assessments is critical to inform adaptation policy actions.

CRediT authorship contribution statement

Nigel C. Sainsbury: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Validation, Visualization, Writing - original draft, Writing - review & editing. **Peter W. Schuhmann:** Formal analysis, Methodology, Supervision, Writing - review & editing. **Rachel A. Turner:** Funding acquisition, Supervision, Writing - review & editing. **Gaetano Grilli:** Formal analysis, Methodology, Writing - review & editing. **John K. Pinnegar:** Funding acquisition, Writing - review & editing. **Martin J. Genner:** Writing - review & editing. **Stephen D. Simpson:** Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

N.C.S. acknowledges the financial support of the UK Natural Environment Research Council (NERC; GW4+ studentships NE/L002434/1), Centre for Environment, Fisheries and Aquaculture Science (DP371Q) and Willis Research Network (NE/L002434/1).

Appendix. – Specification of models

Conditional logit and random parameter logit models can be used to explain choices made based on the attributes of choice alternatives. The modelling approach is based on the assumption that the level of utility derived from an alternative is a function of its attributes (Lancaster, 1966), respondents have perfect information, and choose the alternative that provides them with the greatest utility (that is to say, value or desirability). Under Random Utility Theory, on which choice experiments are generally based, the utility a respondent derives from an alternative is the sum of a systematic and a random component (McFadden, 1973). The deterministic dimension can be estimated based on the data collected, whilst the random dimension is assumed to be known to the respondent but cannot be inferred from the data.

$$U = U(x_i, \ldots, x_m;\ z_i, \ldots, z_m) = V(x, z) + \varepsilon$$

Where U is the utility of the alternative, $x_{i\text{-}m}$ are the alternative's attribute, $Z_{i\text{-}m}$ are characteristics of the individual respondents, V is the deterministic component of utility and ε is the unobserved random component of utility. The probability of a respondent choosing alternative i over alternative j can be expressed as,

$$P(i|C) = P\left(U_i > U_j\right) = P[(V_i + \varepsilon_i) > (V_j + \varepsilon_j)] = P[(V_i - V_j) > (\varepsilon_j - \varepsilon_i)]$$

$$\forall i; j \in C; i \neq j$$

The conditional logit model relies on three assumptions: (1) the random error component is independently and identically distributed (IID) across alternatives (i.e. there is no covariance in between ε_j and ε_i and the variance of ε_j and $\varepsilon_i$are equal); (2) choice alternatives are independent from irrelevant alternatives (IIA), i.e. that the value placed on one alternative is not affected by another alternative within the choice set; and (3) the random error component is type I generalised extreme value (Gumbel) distributed (Hensher et al., 2015b). Under these assumptions, the conditional logit can be expressed as,

$$P(i|C) = \frac{\exp\beta V_i}{\Sigma_{j=1}^{C}\exp\beta V_j}$$

$$\forall i; j \in C; i \neq j$$

Now assuming that V_i, the deterministic portion of utility of an alternative i, is a function of four individual attributes ($x_{1i} - x_{4i}$), weighted by coefficients that define their relative contribution to the utility of the alternative ($\beta_1, \ldots, \beta_4$) then,

$$V_i = ASC + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4$$

The alternative specific constant (*ASC*) is an indicator variable equal to the unobserved utility and included to capture preferences for taking fishing trips versus staying in port.

The random parameter logit model (RPL, also known as mixed logit model) is commonly employed to explain heterogeneity in individual preferences (Hensher and Greene, 2003). The unobserved component of utility (ε) is split into two parts: (1) one is assumed to be correlated across alternatives with non-constant variance and is a random term with a distribution that is defined by observed individual and alternative parameters; and (2) another is a random term as per the conditional logit model, which is IID, IIA and type I extreme value distributed. The choice probability (*P*) in a RPL model is the integral of the mean of a mix of conditional logit functions,

$$P(i|C) = \int \frac{\exp\beta V_i}{\Sigma_{j=1}^{C}\exp\beta V_j} f(\beta)d\beta$$

Where β is a vector of parameter values and the mix of CL functions is defined by a parameter density function, $f(\beta)$.

References

Abernethy, K.E., Trebilcock, P., Kebede, B., Allison, E.H., Dulvy, N.K., 2010. Fuelling the decline in UK fishing communities? ICES. J. Mar. Sci. 67, 1076–1085. https://doi.org/10.1093/icesjms/fsp289.

Acheson, J.M., 1981. Anthropology of fishing. Annu. Rev. Anthropol. 10, 275–316. https://doi.org/10.1146/annurev.an.10.100181.001423.

Adger, W.N., 2006. Vulnerability. Glob. Environ. Chang. 16, 268–281. https://doi.org/10.1016/j.gloenvcha.2006.02.006.

Adger, W.N., Hughes, T.P., Folke, C., Carpenter, S.R., Rockström, J., 2005. Social-ecological resilience to coastal disasters. Science 309, 1036–1039. https://doi.org/10.1126/science.1112122.

Allison, E.H., Perry, A.L., Badjeck, M.C., Neil Adger, W., Brown, K., Conway, D., Halls, A. S., Pilling, G.M., Reynolds, J.D., Andrew, N.L., Dulvy, N.K., 2009. Vulnerability of national economies to the impacts of climate change on fisheries. Fish Fish. 10, 173–196. https://doi.org/10.1111/j.1467-2979.2008.00310.x.

Badjeck, M., Allison, E.H., Halls, A.S., Dulvy, N.K., 2010. Impacts of climate variability and change on fishery-based livelihoods. Mar. Policy 34, 375–383. https://doi.org/10.1016/j.marpol.2009.08.007.

Bastardie, F., Nielsen, J.R., Andersen, B.S., Eigaard, O.R., 2013. Integrating individual trip planning in energy efficiency – Building decision tree models for Danish fisheries. Fish. Res. 143, 119–130. https://doi.org/10.1016/j.fishres.2013.01.018.

Ben-Yami, M. 1987. Purse-seining with small boats, FAO Training Series. FAO, Rome.

Binkley, M, 1995. Toward a safer fishery, in: Risks, Dangers, and Rewards in the Nova Scotia Offshore Fishery. McGill-Queen's University Press, pp. 156–160.

Bech, M., Gyrd-Hansen, D., 2005. Effects coding in discrete choice experiments. Health Econ. 14, 1079–1083. https://doi.org/10.1002/hec.984.

Binkley, M., 1991. Nova Scotian offshore fishermen's awareness of safety. Mar. Policy 15, 170–182. https://doi.org/10.1016/0308-597X(91)90060-O.

Bliemer, M.C.J., Rose, J.M., 2011. Experimental design influences on stated choice outputs: An empirical study in air travel choice. Transp. Res. Part A Policy Pract. 45, 63–79. https://doi.org/10.1016/j.tra.2010.09.003.

Bockstael, N.E., Opaluch, J.J., 1983. Discrete modelling of supply response under uncertainty: The case of the fishery. J. Environ. Econ. Manage. 10, 125–137. https://doi.org/10.1016/0095-0696(83)90021-9.

Brett Hauber, A., Fairchild, A.O., Reed Johnson, F., 2013. Quantifying benefit-risk preferences for medical interventions: An overview of a growing empirical literature. Appl. Health Econ. Health Policy 11, 319–329. https://doi.org/10.1007/s40258-013-0028-y.

Bryman, A., 2012. Sampling. In: .. Oxford University Press, pp. 183–206.

Cheung, W.W.L., Pinnegar, J., Merino, G., Jones, M.C., Barange, M., 2012. Review of climate change impacts on marine fisheries in the UK and Ireland. Aquat. Conserv. Mar. Freshw. Ecosyst. 22, 368–388. https://doi.org/10.1002/aqc.2248.

Cheung, W.W.L., Watson, R., Pauly, D., 2013. Signature of ocean warming in global fisheries catch. Nature 497, 365–368. https://doi.org/10.1038/nature12156.

Choicemetrics, 2018. Ngene 1.2 user manual and reference guide.

Christensen, A.S., Raakjær, J., 2006. Fishermen's tactical and strategic decisions. A case study of Danish demersal fisheries. Fish. Res. 81, 258–267. https://doi.org/10.1016/j.fishres.2006.06.018.

Cinner, J.E., Adger, W.N., Allison, E.H., Barnes, M.L., Brown, K., Cohen, P.J., Gelcich, S., Hicks, C.C., Hughes, T.P., Lau, J., Marshall, N.A., Morrison, T.H., 2018. Building adaptive capacity to climate change in tropical coastal communities. Nat. Clim. Chang. 8, 117–123. https://doi.org/10.1038/s41558-017-0065-x.

Clark, M.D., Determann, D., Petrou, S., Moro, D., de Bekker-Grob, E.W., 2014. Discrete choice experiments in health economics: A review of the literature. Pharmacoeconomics 32, 883–902. https://doi.org/10.1007/s40273-014-0170-x.

Cornwall Rural Community Charity, 2016. Local Development Strategy for Cornwall & Isles of Scilly.

Crabbe, M., Vandebroek, M., 2012. Using appropriate prior information to eliminate choice sets with a dominant alternative from D-efficient designs. J. Choice Model. 5, 22–45. https://doi.org/10.1016/S1755-5345(13)70046-0.

Cull, R., Morduch, J., 2018. Microfinance and economic development. In: Handbook of Finance and Development. https://doi.org/10.4337/9781785360510.00030.

Daly, A., Dekker, T., Hess, S., 2016. Dummy coding vs effects coding for categorical variables: Clarifications and extensions. J. Choice Model. 21, 36–41. https://doi.org/10.1016/j.jocm.2016.09.005.

Davies, T.K., Mees, C.C., Milner-Gulland, E.J., 2014. Modelling the spatial behaviour of a tropical tuna purse seine fleet. PLoS One 9, 1–18. https://doi.org/10.1371/journal.pone.0114037.

de Bekker-Grob, E.W., Ryan, M., Gerard, K., 2012. Discrete choice experiments in health economics: A review of the literature. Heal. Econ. 21, 145–172. https://doi.org/10.1002/hec.1697.

DeShazo, J.R., Fermo, G., 2002. Designing choice sets for stated preference methods: The effects of complexity on choice consistency. J. Environ. Econ. Manage. 44, 123–143. https://doi.org/10.1006/jeem.2001.1199.

Dickson, W., 1993. Estimation of the capture efficiency of trawl gearI: Development of a theoretical model. Fish. Res. 16, 239–253. https://doi.org/10.1016/0165-7836(93)90096-P.

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., Wagner, G.G., 2011. Individual risk attitudes: Measurement, determinants, and behavioral consequences. J. Eur. Econ. Assoc. 9, 522–550. https://doi.org/10.1111/j.1542-4774.2011.01015.x.

Econometrics Software Inc., 2019. NLOGIT6.

Eggert, H., Lokina, R.B., 2007. Small-scale fishermen and risk preferences. Mar. Resour. Econ. 22, 49–67. https://doi.org/10.1086/mre.22.1.42629535.

Ehrich, S., Stransky, C., 1999. Fishing effects in northeast Atlantic shelf seas: patterns in fishing effort, diversity and community structure. VI. Gale effects on vertical distribution and structure of a fish assemblage in the North Sea. Fish. Res. 40, 185–193. https://doi.org/10.1016/S0165-7836(98)00211-2.

Ekstrom, J.A., Suatoni, L., Cooley, S.R., Pendleton, L.H., Waldbusser, G.G., Cinner, J.E., Ritter, J., Langdon, C., Van Hooidonk, R., Gledhill, D., Wellman, K., Beck, M.W., Brander, L.M., Rittschof, D., Doherty, C., Edwards, P.E.T., Portela, R., 2015. Vulnerability and adaptation of US shellfisheries to ocean acidification. Nat. Clim. Chang. 5, 207–214. https://doi.org/10.1038/nclimate2508.

Emery, T.J., Hartmann, K., Green, B.S., Gardner, C., Tisdell, J., 2014. Fishing for revenue: how leasing quota can be hazardous to your health. ICES J. Mar. Sci. 71, 1854–1865. https://doi.org/10.1093/icesjms/fsu019.

FAO, 2019. European Boat Operated Purse Seining. Fishing Techniques, Rome.

FAO, 2016. The state of world fisheries and aquaculture 2016. Contributing to food security and nutrition for all. Rome.

Faugier, J., Sargeant, M., 1997. Sampling hard to reach populations. J. Adv. Nurs. 26, 790–797. https://doi.org/10.1046/j.1365-2648.1997.00371.x.

Feser, F., Barcikowska, M., Krueger, O., Schenk, F., Weisse, R., Xia, L., 2015. Storminess over the North Atlantic and northwestern Europe – A review. Q. J. R. Meteorol. Soc. 141, 350–382. https://doi.org/10.1002/qj.2364.

Fishburn, P.C., 1988. Expected utility: An anniversary and a new era. J. Risk Uncertain. 1, 267–283. https://doi.org/10.1007/BF00056138.

Flizik, A., 2011. Show card. In: Lavrakas, P.J. (Ed.), Encyclopedia of Survey Research Methods. Sage Publications, Inc., pp. 818–819. https://doi.org/10.4135/9781412963947

Forster, J., Schuhmann, P.W., Lake, I.R., Watkinson, A.R., Gill, J.A., 2012. The influence of hurricane risk on tourist destination choice in the Caribbean. Clim. Change 114, 745–768. https://doi.org/10.1007/s10584-012-0433-5.

Fulmer, S., Buchholz, B., Jenkins, P., Scribani, M., 2019. Injuries and exposure to time lobstering in Northeast US inshore lobster fleet. J. Agromedicine 24, 333–340. https://doi.org/10.1080/1059924X.2019.1645780.

Gianelli, I., Ortega, L., Defeo, O., 2019. Modeling short-term fishing dynamics in a small-scale intertidal shellfishery. Fish. Res. 209, 242–250. https://doi.org/10.1016/j.fishres.2018.09.028.

Golden, C.D., Allison, E.H., Dey, M.M., Halpern, B.S., McCauley, Douglas J., Matthew, Smith, Vaitla, B., 2016. Fall in fish catch threatens human health. Nature 534, 317–320. https://doi.org/10.1038/534317a.

Greene, W.H., Hensher, D.A., 2003. A latent class model for discrete choice analysis: Contrasts with mixed logit. Transp. Res. Part B Methodol. 37, 681–698. https://doi.org/10.1016/S0191-2615(02)00046-2.

Griffiths, P., Gossop, M., Powis, B., Strang, J., 1993. Reaching hidden populations of drug users by privileged access interviewers: methodological and practical issues. Addiction 88, 1617–1626. https://doi.org/10.1111/j.1360-0443.1993.tb02036.x.

Hanley, N., Mourato, S., Wright, R.E., 2002. Choice modelling approaches: a superior alternative for environmental valuatioin? J. Econ. Surv. 15, 435–462. https://doi.org/10.1111/1467-6419.00145.

Harrison, M., Rigby, D., Vass, C., Flynn, T., Louviere, J., Payne, K., 2014. Risk as an attribute in discrete choice experiments: A systematic review of the literature. Patient. https://doi.org/10.1007/s40271-014-0048-1.

Hartmann, D.L., Klein Tank, A.M.G., Rusticucci, M., Alexander, L. V., Brönnimann, S., Charabi, Y.A.R., Dentener, F.J., Dlugokencky, E.J., Easterling, D.R., Kaplan, A., Soden, B.J., Thorne, P.W., Wild, M., Zhai, P. 2013. Observations: Atmosphere and surface, in: Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex, P.M.M. (Ed.), Climate Change 2013 the Physical Science Basis: Working Group I Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, Cambridge, pp. 159–254. https://doi.org/10.1017/CBO9781107415324.008.

Hensher, D.A., 2010. Hypothetical bias, choice experiments and willingness to pay. Transp. Res. Part B Methodol. 44, 735–752. https://doi.org/10.1016/j.trb.2009.12.012.

Hensher, D.A., 2006. How do respondents process stated choice experiments? Attribute consideration under varying information load. J. Appl. Econ. 21, 861–878. https://doi.org/10.1002/jae.877.

Hensher, D.A., Greene, W.H., 2003. The mixed logit model: the state of practice. Transportation (Amst). 30, 133–176. https://doi.org/10.1023/A:1022558715350.

Hensher, D.A., Greene, W.H., Li, Z., 2011. Embedding risk attitude and decision weights in non-linear logit to accommodate time variability in the value of expected travel time savings. Transp. Res. Part B Methodol. 45, 954–972. https://doi.org/10.1016/j.trb.2011.05.023.

Hensher, D.A., Rose, J., Greene, W.H., 2005. The implications on willingness to pay of respondents ignoring specific attributes. Transportation (Amst) 32, 203–222. https://doi.org/10.1007/s11116-004-7613-8.

Hensher, D.A., Rose, J.M., Greene, W.H., 2015a. Choice and utility. In: Applied Choice Analysis. Cambridge University Press, Cambridge, pp. 30–79.

Hensher, D.A., Rose, J.M., Greene, W.H., 2015b. Families of discrete choice models. In: Applied Choice Analysis. Cambridge University Press, Cambridge, pp. 80–116.

Holland, D.S., 2008. Are Fishermen rational? A fishing expedition. Mar. Resour. Econ. 23, 325–344. https://doi.org/10.1086/mre.23.3.42629621.

Hoyos, D., 2010. The state of the art of environmental valuation with discrete choice experiments. Ecol. Econ. 69, 1595–1603. https://doi.org/10.1016/j.ecolecon.2010.04.011.

Huchim-Lara, O., Salas, S., Fraga, J., Méndez-Domínguez, N., Chin, W., 2016. Fishermen's perceptions and attitudes toward risk diving and management issues in small-scale fisheries. Am. J. Hum. Ecol. 5, 1–10.

Husni, M.E., Betts, K.A., Griffith, J., Song, Y., Ganguli, A., 2017. Benefit-risk trade-offs for treatment decisions in moderate-to-severe rheumatoid arthritis: focus on the patient perspective. Rheumatol. Int. 37, 1423–1434. https://doi.org/10.1007/s00296-017-3760-z.

Jacklin, M., Combes, J., 2007. The Good Practice Guide to Handling and Storing Live Crustacea. Seafish, Edinburgh.

Jensen, O.C.C., Petursdottir, G., Holmen, I.M. ari., Abrahamsen, A., Lincoln, J. 2014. A review of fatal accident incidence rate trends in fishing. Int. Marit. Health 65, 47–52. https://dx.doi.org/10.5603/IMH.2014.0011.

Jin, D., Thunberg, E., 2005. An analysis of fishing vessel accidents in fishing areas off the northeastern United States. Saf. Sci. 43, 523–540. https://doi.org/10.1016/j.ssci.2005.02.005.

Johnson, F. Reed, Lanscar, Emily, Marshall, Deborah, Kilambi, Vikram, Mühlbacher, Axel, Regier, Dean, Bresnahan, Brian, Kanninen, Barbara, Bridges, John, 2013. Constructing experimental designs for discrete-choice experiments: report of the ISPOR Conjoint Analysis Experimental Design Good Research Practices Task Force. Value Health 16 (1), 3–13. https://doi.org/10.1016/j.jval.2012.08.2223.

Johnston, R.J., Boyle, K.J., Vic Adamowicz, W., Bennett, J., Brouwer, R., Ann Cameron, T., Michael Hanemann, W., Hanley, N., Ryan, M., Scarpa, R., Tourangeau, R., Vossler, C.A., 2017. Contemporary guidance for stated preference studies. J. Assoc. Environ. Resour. Econ. 4, 319–405. https://doi.org/10.1086/691697.

Kahneman, D., Tversky, A., 1992. Advances in prospect theory: Cumulative representation of uncertainty. J. Risk Uncertain. 5, 297–323. https://doi.org/10.1007/BF00122574.

Keeling, R.F., Körtzinger, A., Gruber, N., 2010. Ocean deoxygenation in a warming world. Ann. Rev. Mar. Sci. 2, 199–229. https://doi.org/10.1146/annurev.marine.010908.163855.

Kløjgaard, M.E., Bech, M., Søgaard, R., 2012. Designing a stated choice experiment: The value of a qualitative process. J. Choice Model. 5, 1–18. https://doi.org/10.1016/S1755-5345(13)70050-2.

Kossin, J.P., Knapp, K.R., Olander, T.L., Velden, C.S., 2020. Global increase in major tropical cyclone exceedance probability over the past 40 years. Proc. Natl. Acad. Sci. U.S.A. 117, 11975–11980. https://doi.org/10.1073/pnas.1920849117.

Lancaster, K., 1966. A new approach to consumer theory. J. Polit. Econ. 74, 132–157. https://doi.org/10.1086/259131.
Lê, S., Josse, J., Husson, F. 2008. FactoMineR: An R Package for Multivariate Analysis. J. Stat. Softw. 25, 1–18. https://dx.doi.org/10.18637/jss.v025.i01.
Li, B., Hensher, D.A., 2017. Risky weighting in discrete choice. Transp. Res. Part B Methodol. 102, 1–21. https://doi.org/10.1016/j.trb.2017.04.014.
Lincoln, J.M., Lucas, D.L., 2010. Occupational fatalities in the United States commercial fishing industry, 2000–2009. J. Agromed. 15, 343–350. https://doi.org/10.1080/1059924X.2010.509700.
Lopes, P.F.M., Begossi, A., 2011. Decision-making processes by small-scale fishermen on the southeast coast of Brazil. Fish. Manag. Ecol. 18, 400–410. https://doi.org/10.1111/j.1365-2400.2011.00795.x.
Louviere, J. 2000. Introduction to stated preference models and methods, in: Stated Choice Methods Analysis and Applications. Cambridge University Press, Cambridge, pp. 20–33. https://dx.doi.org/10.1017/CBO9780511753831.002.
Macusi, E.D., Babaran, R.P., van Zwieten, P.A.M., 2015. Strategies and tactics of tuna fishers in the payao (anchored FAD) fishery from general Santos city. Philippines. Mar. Policy 62, 63–73. https://doi.org/10.1016/j.marpol.2015.08.020.
Main, J., Sangster, G. 1981. A study of the sand clouds produced by trawl boards and their possible effect on fish capture, Scottish Fisheries Research Report. Department of Agriculture and Fisheries for Scotland, Marine Laboratory, Aberdeen.
Marine Management Organisation (MMO), 2019a. Latest dataset UK and foreign vessels landings by UK port and UK vessel landings abroad: 2014 to 2018 and 2019 (year to date). https://www.gov.uk/government/statistical-data-sets/uk-and-foreign-vessels-landings-by-uk-port-and-uk-vessel-landings-abroad (accessed 9.23.19).
Marine Management Organisation (MMO), 2019b. UK fishing vessel lists https://www.gov.uk/government/collections/uk-vessel-lists (accessed 9.23.19).
Marine Scotland Science, 2014. Scottish Sea Fisheries Employment 2013.
Marshall, N.A., Tobin, R.C., Marshall, P.A., Gooch, M., Hobday, A.J., 2013. Social vulnerability of marine resource users to extreme weather events. Ecosystems 16, 797–809. https://doi.org/10.1007/s10021-013-9651-6.
Mata, R., Josef, A.K., Hertwig, R., 2016. Propensity for risk taking across the life span and around the globe. Psychol. Sci. 27, 231–243. https://doi.org/10.1177/0956797615617811.
McCarthy, J.J., Canziani, O.F., Leary, N.A., Dokken, D.J., White, K.S., 2001. Climate Change 2001: Impacts, Adaptation, and Vulnerability, Contribution of Working Group II to the Third Assessment Report of the Intergovernmental Panel on Climate Change. Camridge University Press, Cambridge.
McDonald, M.A., Kucera, K.L., 2007. Understanding non-industrialized workers' approaches to safety: How do commercial fishermen "stay safe"? J. Safety Res. 38, 289–297. https://doi.org/10.1016/j.jsr.2006.10.009.
McFadden, D., 1973. Conditional logit analysis of qualitative choice behaviour. In: Zarembka, P. (Ed.), Frontiers of Econometrics. Academic Press, New York, pp. 105–142.
McWilliams, J., 2014. The Cornish Fishing Industry, An Illustrated History. Amberley Publishing, Stroud.
Metcalf, S.J., van Putten, E.I., Frusher, S., Marshall, N.A., Tull, M., Caputi, N., Haward, M., Hobday, A.J., Holbrook, N.J., Jennings, S.M., Pecl, G.T., Shaw, J., 2015. Measuring the vulnerability of marine social-ecological systems: A prerequisite for the identification of climate change adaptations. Ecol. Soc. 20, 35. https://doi.org/10.5751/ES-07509-200235.
Mishra, S., Lalumière, M.L., 2010. You can't always get what you want: The motivational effect of need on risk-sensitive decision-making. J. Exp. Soc. Psychol. 46, 605–611. https://doi.org/10.1016/j.jesp.2009.12.009.
Mistiaen, J.A., Strand, I.E., 2000. Spatial models in fisheries economics -location choice of commercial fishermen with heterogenous risk preferences. Am. J. Agric. Econ. 82, 1184–1190. https://doi.org/10.1111/0002-9092.00118.
Mölter, T., Schindler, D., Albrecht, A.T., Kohnle, U., 2016. Review on the projections of future storminess over the North Atlantic European region. Atmosphere (Basel) 7, 1–40. https://doi.org/10.3390/atmos7040060.
Monnereau, I., Mahon, R., McConney, P., Nurse, L., Turner, R., Vallès, H., 2017. The impact of methodological choices on the outcome of national-level climate change vulnerability assessments: An example from the global fisheries sector. Fish Fish. 18, 717–731. https://doi.org/10.1111/faf.12199.
Morel, G., Amalberti, R., Chauvin, C., 2008. Articulating the differences between safety and resilience: The decision-making process of professional sea-fishing skippers. Hum. Factors J. Hum. Factors Ergon. Soc. 50, 1–16. https://doi.org/10.1518/001872008x250683.
Mühlbacher, A., Reed Johnson, F., 2016. Choice experiments to quantify preferences for health and healthcare: state of the practice. Appl. Health Econ. Health Policy 14, 253–266. https://doi.org/10.1007/s40258-016-0232-7.
Muir, W.D., Durkin, J.T., Coley, T.C., Mccabe, G.T., 1984. Escape of captured dungeness crabs from commercial crab pots in the Columbia River Estuary. North Am. J. Fish. Manag. 4, 552–555. https://doi.org/10.1577/1548-8659(1984)4<552:eocdcf>2.0.co;2.
Murakami, H., Vecchi, G.A., Underwood, S., 2017. Increasing frequency of extremely severe cyclonic storms over the Arabian Sea. Nat. Clim. Chang. 7, 885–889. https://doi.org/10.1038/s41558-017-0008-6.
Murphy, G.I., 1959. Effect of water clarity on Albacore catches. Limnol. Oceanogr. 4, 86–93. https://doi.org/10.4319/lo.1959.4.1.0086.
Naranjo-Madrigal, H., van Putten, I., Norman-López, A., 2015. Understanding socio-ecological drivers of spatial allocation choice in a multi-species artisanal fishery: A Bayesian network modeling approach. Mar. Policy 62, 102–115. https://doi.org/10.1016/j.marpol.2015.09.003.
Niclasen, B.A., Simonsen, K., Magnusson, A.K., 2010. Wave forecasts and small-vessel safety: A review of operational warning parameters. Mar. Struct. 23, 1–21. https://doi.org/10.1016/j.marstruc.2010.02.001.
Olin, M., Kurkilahti, M., Peitola, P., Ruuhijärvi, J., 2004. The effects of fish accumulation on the catchability of multimesh gillnet. Fish. Res. 68, 135–147. https://doi.org/10.1016/j.fishres.2004.01.005.
Orme, B.K., 2010. Sample size issues for conjoint analysis. In: Research Publishers, L.L.C. (Ed.), Getting Started with Conjoint Analysis: Strategies for Product Design and Pricing Research. Madison, Wisconsin, pp. 57–66.
Ostrom, E., 2009. A general framework for analyzing sustainability of social-ecological systems. Science 325, 419–422. https://doi.org/10.1126/science.1172133.
Pinnegar, J.K., Engelhard, G.H., Norris, N.J., Theophille, D., Sebastien, R.D., 2019. Assessing vulnerability and adaptive capacity of the fisheries sector in Dominica: Long-term climate change and catastrophic hurricanes. ICES J. Mar. Sci. 76, 1353–1367. https://doi.org/10.1093/icesjms/fsz052.
Plagányi, É., 2019. Climate change impacts on fisheries. Science 363, 930–931. https://doi.org/10.1126/science.aaw5824.
Poggie, J.J., Pollnac, R.B., Van Dusen, C., 1996. Intracultural variability in the cognition of danger among southern new England fishers. Mar. Resour. Econ. 11, 23–30. https://doi.org/10.1086/mre.11.1.42629140.
Puckett, S.M., Hensher, D.A., 2008. The role of attribute processing strategies in estimating the preferences of road freight stakeholders. Transp. Res. Part E Logist. Transp. Rev. 44, 379–395. https://doi.org/10.1016/j.tre.2007.01.002.
Queirolo, D., Straley, J., Connell, V.O., Liddle, J., Thode, A., Wild, L., Behnken, L., Falvey, D., Lunsford, C., 2015. Effects of environmental conditions and fishing operations on the performance of a bottom trawl. ICES J. Marine Sci. 69, 293–302. https://doi.org/10.1093/icesjms/fsr211.
R CoreTeam, 2019. R: A Language and Environment for Statistical Computing.
Rezaee, S., Pelot, R., Finnis, J., 2016. The effect of extratropical cyclone weather conditions on fishing vessel incidents' severity level in Atlantic Canada. Saf. Sci. 85, 33–40. https://doi.org/10.1016/j.ssci.2015.12.006.
Roalf, D.R., Mitchell, S.H., Harbaugh, W.T., Janowsky, J.S., 2012. Risk, reward, and economic decision making in aging. J. Gerontol. Ser. B Psychol. Sci. Soc. Sci. 67, 289–298. https://doi.org/10.1093/geronb/gbr099.
Roberts, S.E., 2010. Britain's most hazardous occupation: Commercial fishing. Accid. Anal. Prev. 42, 44–49. https://doi.org/10.1016/j.aap.2009.06.031.
Rose, J.M., Bliemer, M.C.J., Hensher, D.A., Collins, A.T., 2008. Designing efficient stated choice experiments in the presence of reference alternatives. Transp. Res. Part B Methodol. 42, 395–406. https://doi.org/10.1016/j.trb.2007.09.002.
Sainsbury, N.C., Genner, M.J., Saville, G.R., Pinnegar, J.K., O'Neill, C.K., Simpson, S.D., Turner, R.A., 2018. Changing storminess and global capture fisheries. Nat. Clim. Chang. 8, 655–659. https://doi.org/10.1038/s41558-018-0206-x.
Sainsbury, N.C., Turner, R.A., Townhill, B.L., Mangi, S.C., Pinnegar, J.K., 2019. The challenges of extending climate risk insurance to fisheries. Nat. Clim. Chang. 9, 896–897. https://doi.org/10.1038/s41558-019-0645-z.
Scarpa, R., Rose, J.M., 2008. Design efficiency for non-market valuation with choice modelling: How to measure it, what to report and why. Aust. J. Agric. Resour. Econ. 52, 253–282. https://doi.org/10.1111/j.1467-8489.2007.00436.x.
Scarpa, R., Zanoli, R., Bruschi, V., Naspetti, S., 2013. Inferred and stated attribute non-attendance in food choice experiments. Am. J. Agric. Econ. 95, 165–180. https://doi.org/10.1093/ajae/aas073.
Schnier, K.E., Horrace, W.C., Felthoven, R.G., 2009. The value of statistical life: Pursuing the deadliest catch. Cent. Policy Res. 49 https://doi.org/10.2139/ssrn.1807236.
Shepperson, J., Murray, L.G., Mackinson, S., Bell, E., Kaiser, M.J., 2016. Use of a choice-based survey approach to characterise fishing behaviour in a scallop fishery. Environ. Model. Softw. 86, 116–130. https://doi.org/10.1016/j.envsoft.2016.09.013.
Smith, M.D., Wilen, J.E., 2005. Heterogeneous and correlated risk preferences in commercial fishermen: The perfect storm dilemma. J. Risk Uncertain. 31, 53–71. https://doi.org/10.1007/s11166-005-2930-7.
Somerton, D.A., 2003. Bridle efficiency of a survey trawl for flatfish: Measuring the length of the bridles in contact with the bottom. Fish. Res. 60, 273–279. https://doi.org/10.1016/S0165-7836(02)00178-9.
Stewart, I.J., Keller, A.A., Fruh, E.L., Simon, V.H., Horness, B.H., 2010. Throwing in the towel: When do adverse conditions dictate a weather day during a bottom trawl survey? Fish. Res. 102, 130–140. https://doi.org/10.1016/j.fishres.2009.11.001.
Stobart, B., Mayfield, S., Carroll, J., 2016. Influence of wind and swell on catch rates in a dive fishery: A case study from the south Australian abalone fishery. J. Shellfish Res. 35, 685–694. https://doi.org/10.2983/035.035.0315.
Surminski, S., Bouwer, L.M., Linnerooth-bayer, J., 2016. How insurance can support climate resilience. Nat. Clim. Chang. 6, 333–334. https://doi.org/10.1038/nclimate2979.
UK Office for National Statistics (ONS), 2017. CT0724_2011 Census Age by General Health by Industry (2 Digits). URL https://www.ons.gov.uk/employmentandlabourmarket/peoplenotinwork/economicinactivity/adhocs/007524ct07242011censusagebygeneralhealthbyindustry2digits (accessed 11.20.18).
Urquhart, J., Acott, T., Reed, M., Courtney, P., 2011. Setting an agenda for social science research in fisheries policy in Northern Europe. Fish. Res. 108, 240–247. https://doi.org/10.1016/j.fishres.2010.12.026.
van der Pol, M., Shiell, A., Au, F., Jonhston, D., Tough, S., 2010. Eliciting individual preferences for health care: A case study of perinatal care. Heal. Expect. 13, 4–12. https://doi.org/10.1111/j.1369-7625.2009.00551.x.
Van Houtven, G., Johnson, F.R., Kilambi, V., Hauber, A.B., 2011. Eliciting benefit-risk preferences and probability-weighted utility using choice-format conjoint analysis. Med. Decis. Mak. 31, 469–480. https://doi.org/10.1177/0272989X10386116.

van Nieuwkoop, J.C.C., Smith, H.C.M., Smith, G.H., Johanning, L., 2013. Wave resource assessment along the Cornish coast (UK) from a 23-year hindcast dataset validated against buoy measurements. Renew. Energy 58, 1–14. https://doi.org/10.1016/j.renene.2013.02.033.

van Putten, I.E., Kulmala, S., Thébaud, O., Dowling, N., Hamon, K.G., Hutton, T., Pascoe, S., 2012. Theories and behavioural drivers underlying fleet dynamics models. Fish Fish. 13, 216–235. https://doi.org/10.1111/j.1467-2979.2011.00430.x.

Weinberg, K.L., Kotwicki, S., 2015. Reducing variability in bottom contact and net width of a survey trawl by restraining door movement and applying a constant ratio of warp length to depth. Fish. Bull. 113, 180–190. https://doi.org/10.7755/FB.113.2.6.

Wu, Y., Pelot, R., Hilliard, C., 2005. The effect of weather factors on the severity of fishing boat accidents in Atlantic Canada. Risk Manag. 7, 21–40. https://doi.org/10.1057/palgrave.rm.8240217.

Wu, Y., Pelot, R.P., Hilliard, C., 2009. The influence of weather conditions on the relative incident rate of fishing vessels. Risk Anal. 29, 985–999. https://doi.org/10.1111/j.1539-6924.2009.01217.x.

Zhou, S., Shirley, T.C., 1997. Behavioural responses of red king crab to crab pots. Fish. Res. 30, 177–189. https://doi.org/10.1016/S0165-7836(97)00005-2.